Investigating The Moderating Effect Of Demographic Variables On People Analytics And Employee Performance

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ARTICLE INFO	ABSTRACT
	This study examines how demographic characteristics including age, gender, education, and experience moderate the People Analytics-employee performance link. It investigates how demographic characteristics affect data-drivenHR practices and employee performance. The study explores whether demographic factors affect the link between People Analytics and Employee Performance, using ethical principles. The study examines demographic variable moderating effects using regression and moderation analysis. Key construct measuring instruments are thoroughly tested for reliability and validity. The quantitative research study uses [PLS-SEM] for data analysis since it meets its goals. Initial study suggests that key construct measuring devices are reliable and valid. Demographic characteristics affect People Analytics' influence on employee performance, and the research sheds light on their complex linkages. This article concludes that demographic characteristics are crucial to People Analytics programs' success, contributing to HR and organizational research. It helps HR professionals create focused interventions for their varied workforce. The study emphasizes research integrity andparticipant rights. **Keywords—** Demographics characteristics, Employee Performance, People Analytics, Ethical principles, Moderation Analysis, Organizational Research

I. INTRODUCTION

In today's rapidly evolving business landscape, organizations are continually seeking innovative ways to optimize their human resources and enhance overall performance. The emergence of People Analytics, a data-driven approach to HR management, has gained considerable attention as a means to achieve this goal. People Analytics leverages advanced data analytics techniques to mine valuable insights from HR data, enabling organizations to make informed decisions about their workforce strategies This shift towards evidence-based HR practices holds the promise of improving employee performance, a central concern for organizations aiming to remain competitive and adaptive in the modern marketplace.[1]

Employee performance is a multifaceted construct that encompasses individual and collective contributions to an organization's goals and objectives. While prior research has established the positive impact of People Analytics on employee performance there isa notable gap in our understanding of how demographic variables, such as age, gender, education, and experience, may interact with People Analytics initiatives to influence performance outcomes.[2] This knowledge gap is significant, as organizations increasingly embrace diversity and inclusion asintegral components of their HR strategies, necessitating a nuanced understanding of how workforce diversity factors into the effectiveness of People Analytics

1.1. STATEMENT OF THE PROBLEM
The central problem addressed in this research is the need toinvestigate the moderating role of demographic variables in shaping the relationship between People Analytics and employee performance. . As organizations endeavor to harness the power of data-driven HR practices, it is paramount to consider how demographic characteristics of employees may affect the impact of these practices[3]. For instance, younger and older employees may respond differently to performance interventions guidedby People Analytics, as may male and female employees or those with varying levels of education and experience. Therefore, understanding the

moderating effects of demographic variables on this relationship is critical for organizations seeking to tailor their HR strategies to the unique needs and characteristics of their workforce.[4]

1.2. RESEARCH OBJECTIVES

- To examine the nature of the relationship between People Analytics and employee performance.
- To assess the moderating effects of demographic variables (age, gender, education, experience) on the relationship between People Analytics and employee performance.
- To identify specific demographic factors that exert a more pronounced moderating influence on the People Analytics-employee performance relationship.

1.3 PEOPLE ANALYTICS IMPORTANCE IN HR AND ORGANIZATIONAL DECION MAKING TO EVALUATE EMPLOYEE PERFORMANCE

People analytics is crucial for HR professionals to predict
employee turnover, optimize recruitment, enhance engagement, and align HR strategies with business goals. It helps identify efficient recruitment channels, improve candidate selection, and enhance job satisfaction and productivity. Factors influencing performance include individual skills, organizational culture, leadership style, training programs, and environmental conditions[5]

Individual Factors: These include an employee's skills, knowledge, motivation, and attitude, which significantly impact their performance[6]. Additionally, individual factors encompass an employee's ability to set goals and self-regulate their behavior.

(a) *Organizational Factors:* The organizational culture, leadership style, training and development programs, and feedback mechanisms directly shape employee performance[7]. These factors establish the context in which employees operate.

(b) *Environmental Factors:* External factors, such as economic conditions, industry trends, and market competition, can influence employee performance[8]. Environmental factors provide the backdrop against which organizational performance is evaluated.

1.4. MODERATING EFFECTS IN RESEARCH

Moderation theory suggests that the relationship between two variables is influenced by a third variable, such as demographic factors like age and education level. This theory is crucial in HR research for understanding complex relationships, customizing practices, and improving predictive accuracy [9]

The concept of moderation holds profound relevance in the field of HR and organizational research for several compelling reasons:

Enhanced Insights into Complex Relationships: Moderation analysis allows researchers to gain deeper insights into the intricate relationships between variables. In HR and organizational contexts, where numerous factors are at play, moderation helps uncover nuanced patterns that might otherwise go unnoticed.

Customization of HR Practices: Understanding moderating effects empowers HR professionals to tailor their strategies more effectively. For instance, knowing how demographic variables moderate the impact of HR practices enables the design of targeted interventions to cater to diverse employee groups[10].

Improved Predictive Accuracy: By incorporating moderation in research models, HR and organizational researchers can enhance the predictive accuracy of their models. This is of particular value to decision-makers seeking to make data-driven, evidence-based decisions in HR management .[11]

In summary, moderation is a crucial concept in HR and organizational research. It offers a valuable lens through which researchers and practitioners can gain deeper insights into the multifaceted relationships between variables and make more informed decisions.

1.5. THEORETICAL FRAMEWORK

The study investigates the influence of demographic factors like age, gender, education, and experience on the relationship between People Analytics interventions and employee performance outcomes, suggesting that these factors can either enhance or mitigate their effect [12]

1.6. DEMOGRAPHIC VARIABLES

Demographic variables like age, gender, education, and experience significantly influence employee behavior and performance in People Analytics projects. Older, longer-tenured workers respond better, while balanced gender representation boosts work happiness and productivity. This research offers practical insights for HR professionals, fosters diversity, advances academic understanding, and has economic implications for organizations[12][13].

In the Expectancy expectations about results affect performance and effort. Demographic variables might moderate this paradigm since various demographic groups may have varied expectations and appraisals of

People Analytics outputs. These theoretical frameworks explain how Demographic Variables and People Analytics affect employee performance and engagement. Demographic variables, such as age, gender, education, and experience, are essential components in understanding the dynamics of employee performance and its relationship with People Analytics. These variables represent inherent characteristics of individuals within an organization and can significantly impact their behavior and performance outcomes.

Age: Age is a fundamental demographic variable known to influence how employees respond to HR practices. In contrast, younger employees may have different expectations and preferences regarding HR interventions.

Gender: Gender diversity in the workplace has gained considerable attention. Gender can moderate the effect of People Analytics on performance. For instance, female employees may respond differently to certain data-driven interventions compared to their male counterparts, influencing their performance outcomes.

*Education***:** The level of education is another demographic variable that can shape employee responses to People Analytics. Research by [14] demonstrated that employees with higher educational qualifications may have a more favorable perception of data-driven HR practices, potentially leading to enhanced performance.

Experience: Years of work experience can significantly impact an employee's ability to adapt to and utilize People Analytics effectively. Experienced employees tend to leverage data-driven insights more efficiently, leading to improved performance outcomes.

Demographic variables play a pivotal role in influencing employee performance. The impact of these variables can be both direct and moderating. For instance, age-related differences in work attitudes and preferences may influence how employees respond to People Analytics initiatives. Similarly, gender and educational backgrounds can shape employees' expectations and perceptions of HR practices, consequently affecting their performance

In sum, this research transcends the boundaries of a single study and resonates on multiple levels. It offers practical insights for HR professionals, fosters diversity and inclusion, advances academic understanding, and carries economic implications for organizations at large. In a rapidly evolving HR landscape, where data is king and demographic diversity is a driving force, this study is poised to make a lasting impact by empowering organizations to navigate the complex terrain of HR management with greater precision and success.

These studies demonstrate how Demographic Variables may increase or decrease People Analytics' effect on employee performance. Many theoretical frameworks describe how Demographic Variables, People Analytics, and Employee Performance interact. The Social Identity Theory states that people organize themselves by demographics. This idea indicates that demographic group affiliations may affect how workers perceive data-driven interventions in People Analytics, affecting performance and engagement.

2. Literature Review

2.1. INTRODUCTION TO PEOPLE ANALYTICS
People Analytics, also known as HR Analytics or Talent Analytics, is a transformative concept in HRM and organizational decision-making, influenced by scholarly contributions.
In the realm of Human Resource Management (HRM) and organizational decision-making, People Analytics, often referred to as HR Analytics or Talent Analytics, holds a pivotal position as a transformative concept. This section provides an overview of People Analytics, encompassing its definitions, evolution, and its central role within contemporary HRM, while emphasizing the scholarly contributions that have shaped this field.

(a) Definition and Evolution
People Analytics is a systematic HR data analysis method that transforms traditional practices into evidence-based strategies by integrating big data and analytics tools into decision-making in HR departments. [15]
The evolution of People Analytics is intrinsically tied to technological advancements, particularly the emergence of big data and the maturation of data analytics tools. The proliferation of HR data necessitated the development of innovative methods for extracting valuable insights from this reservoir of information. Consequently, People Analytics emerged as a transformative response to this need, revolutionizing HR practices by seamlessly integrating data science into the decision-making fabric of HR departments.

(b) Attraction
People analytics projects can enhance workforce performance, decision-making, and efficiency, attracting more candidates. Companies with robust people analytics programs can recruit and manage diverse talent, anticipate performance, optimize personnel management, and optimize job matching. Despite concerns about data privacy and analytics, people analytics can effectively explain its benefits to potential employees, influence organizational membership choices, foster a data-driven culture, and enhance competitiveness and innovation [16]
These articles discuss people analytics' pros and cons in explaining its benefits to prospective hires. These publications demonstrate that people analytics can successfully explain its advantages to prospective workers, although there are hurdles and concerns.

The research suggest people analytics affect organization membership choices. [12]found that sponsoring an analytical culture, where employees understand top management's decisions and are encouraged to ask questions, produces a data-driven culture. Maximizing talent using people analytics may enhance competitiveness and innovation employing data analytics in recruitment and workforce management to improve the workforce. A 2017 quick-service case study illustrates how people analytics mayprovide talent and performance insights. These publications show that data-driven decision-making and superior workforce management help people analytics-focused organizations acquire talent.

(c) Attrition
People analytics can reduce employee turnover by combining machine learning and deep data, predicting educational personnel turnover, and enhancing human resourcemanagement and job satisfaction. It can also enhance employee happiness and reduce attrition. HR management can use analytics like Power BI and logistic regression to study employee turnover, while analytics like Random Forest and AdaBoost guide retention

Job Performance in terms of Job Quality
Studies show that work happiness, organizational culture, contentment, leadership style, job satisfaction, and superior people managers significantly impact employee performance. People Analytics tools and processes are essential for improving decision-making and employee satisfaction. Strong person-job fit enhances career growth perception, while organizational identity moderates this effect. Support from coworkers and superiors also influencesjob satisfaction. Understanding demographic variables is crucial for organizations to tailor HR strategies and implement People Analytics initiatives

Strong person-job fit may increase workers' perception of internal career growth but decrease their perception of external ones, according to Sirén 2018. Bai 2018 found that career development promotes work engagement and organizational identity, with organizational identity somewhat moderating the effect. Career progression and organizational identity are moderated by person-organizationvalue fit. These studies suggest career advancement promotesemployee engagement and business identity.

Job happiness depends on support and appreciation from coworkers and superiors. Stresses the importance of work happiness by offering promotions and praising employees. Qureshi 2017 shows that supervisor support directly affects work satisfaction and fairness perception moderates it. Employee sense of organizational support affects work life quality and performance.

3. Research Methodology

A study uses quantitative research to examine demographic characteristics' impact on People Analytics and Employee Performance, using standardized data for rigorous hypothesistesting.
The study will use surveys to gather data on People Analytics effectiveness, employee performance, and demographic variables. Secondary data will validate primary data, and statistical analysis will examine the moderating effects of demographic factors on People Analytics and Employee Performance.

Quantitative research design's objectivity, generalizability, and statistically robust conclusions fit the study's goal of examining demographic variables' moderating role in PeopleAnalytics and Employee Performance.

In the pursuit of investigating the moderating role of demographic variables on the relationship between People Analytics and Employee Performance, a combination of primary and secondary data collection methods will be employed.

The combination of stratified random sampling and appropriate sample size determination ensures that the study'sfindings are both representative of the target population and statistically robust. The measurement of demographic variables plays a pivotal role in understanding the moderating effects of these variables on the relationship between People Analytics and Employee Performance. The demographic variables considered include age, gender, education, andyears of experience.

Age: Age will be measured as a continuous variable, with participants asked to provide their age in years. This measureallows for a precise assessment of age-related effects on the research outcomes.

Gender: Gender will be measured as a categorical variable, with response options including "male," "female," and "other" or "prefer not to say." This categorical measure captures the gender diversity within the sample.

Education: Education level will be assessed using a categorical measure,with response options ranging from "high school diploma orequivalent" to "postgraduate degree." This measure providesinsight into participants' educational backgrounds.

Years of Experience: Years of work experience will be measured as a continuous variable, with participants asked toindicate the number of years they have worked in their current field or profession.

Regression Analysis: Initially, multiple regression analysis will be employed to assess the direct relationship between People Analytics and Employee Performance while controlling for potential confounding variables. This analysis will provide insights into the overall impact of People Analytics on employee performance outcomes

Moderation Analysis: This research aims to explore the influence of demographic variables on the relationship between People Analytics and Employee Performance usinghierarchical moderation analysis. This study uses moderation analysis to examine the relationship between People Analytics, demographic characteristics, and employee performance outcomes. Data analysis software, [PLS-SEM], will be used to ensure validity and reliability. The research aims to improve HR management in modern organizations by providing comprehensive statistical tools for regression analysis and moderation analysis.

3.1 ETHICAL CONSIDERATIONS
The study prioritizes participant autonomy, informed consent, and clear understanding of study goals, methods, risks, benefits, and leave-at-anytime options, while maintaining participant privacy and confidentiality through anonymization and ethical data management (Flick, 2018). The permission form will explain these things in straightforward terms. The data collecting technique willdetermine whether consent is sought by signing a form or electronically.

These ethical concerns demonstrate the commitment to conducting this study with honesty and protecting participants' rights and well-being.

II. RESULTS AND DISCUSSION

4.1.PRESENTATION OF DATA
The research presents systematically collected data on People Analytics, Employee Performance, and Demographic Variables, using visual aids like tables and graphs for clarityand accessibility.

4.2. DESCRIPTIVE STATISTICS
Descriptive statistics will be used to provide a comprehensiveoverview of the collected data, using measures like means, standard deviations, and frequency distributions (Hair et al., 2018).

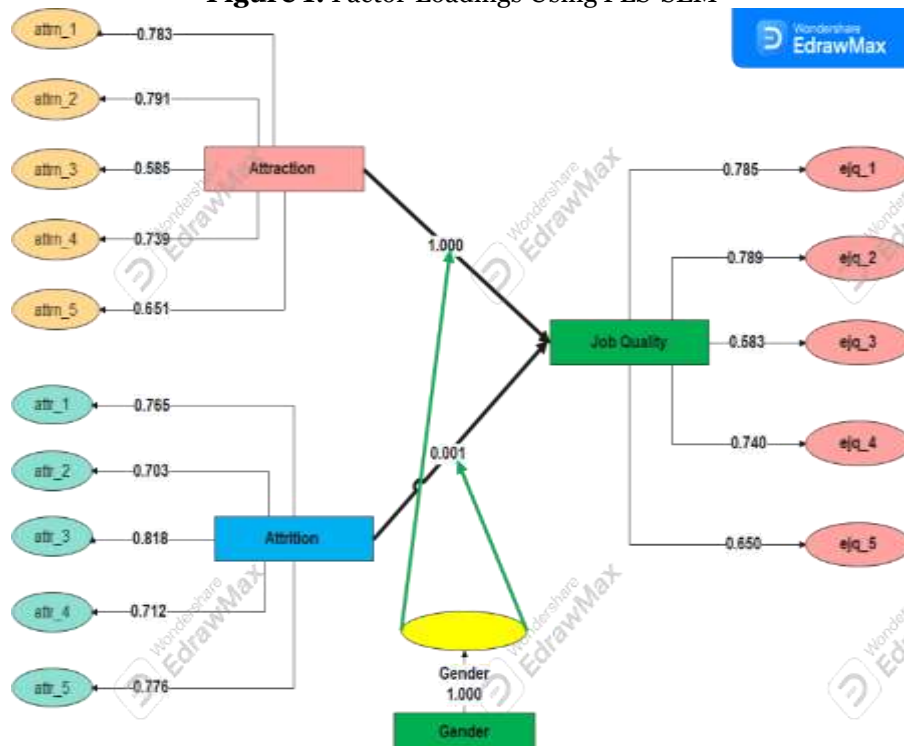**Figure 1:** Factor Loadings Using PLS-SEM

Table 1: Factor Loadings

	Attraction	Attrition	Gender	Job quality	Gender x Attraction	Gender x Attrition
Gender			1			
attr_1		0.765				
attr_2		0.703				
attr_3		0.818				
attr_4		0.712				
attr_5		0.776				
attrn_1	0.783					
attrn_2	0.791					
attrn_3	0.585					
attrn_4	0.739					
attrn_5	0.651					
ejq_1				0.785		
ejq_2				0.789		
ejq_3				0.583		
ejq_4				0.74		
ejq_5				0.65		
Gender x Attraction					1	
Gender x Attrition						1

Sources: Author's estimates

Explanation: The research focuses on the account the different loadings of the items in the construct. Again, values above 0.7 are generally considered good. Average Variance Extracted (AVE): This is a measure of convergent validity, that is, the extent to which a construct is truly measuring what it is intended to measure. A value above 0.5 indicates good convergent validity.

Looking at the values in the table 3. For all three constructs, Cronbach's Alpha and Composite Reliability measures are above 0.7, indicating good internal consistency. The AVE for all constructs is above 0.5, indicating good convergent validity.
constructs of Attraction, Attrition, and Job Quality, and their relationship with Gender. The factor loadings for each item within these constructs indicate how well each item measures the intended construct.

In the Attraction construct, all items (attr_1 to attr_5) have factor loadings above 0.7, suggesting that these items are good indicators of the Attraction construct. Similarly, in the Attrition and Job Quality constructs, all items have factor loadings above 0.5, indicating that these items are reasonably good indicators of their respective constructs. The correlation of 1 between Gender and itself is expected, as any variable will have a perfect positive correlation with itself. The same applies to the interaction terms (Gender x Attraction, Gender x Attrition).

Table 2: R-square and adjusted R-square

	R-square	R-square adjusted
Job quality	1	1

Sources: Author's estimates

In this case, both the R-square and adjusted R-square values for Job Quality are 1.000. This suggests that the model perfectly predicts Job Quality, and all the predictors in the model contribute significantly to this prediction.

However, an R-square or adjusted R-square of 1.000 is extremely rare in practice and might indicate overfitting, especially if it has a large number of predictors in the model. Overfitting is when the model fits the data too well, capturing not only the underlying structure but also the noise. This can lead to poor generalization to new data. In conclusion, while the R-square and adjusted R-square values suggest that model is a perfect fit for the data.

Explanation: The table provided contains reliability and validity measures for three constructs: Attraction, Attrition, and Job Quality. These measures are commonly used in psychometrics and survey research to assess the quality of measurement instruments, such as questionnaires.

Table 3: *Cronbach alpha*

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Attraction	0.755	0.769	0.837	0.51
Attrition	0.814	0.836	0.869	0.571
Job quality	0.755	0.77	0.837	0.51

Sources: Author's estimates

Cronbach's Alpha: This is a measure of internal consistency, that is, how closely related a set of items are as a group. A high value (above 0.7) indicates good internal consistency. Composite Reliability (rho_and rho_c): These are also measures of internal consistency, but they are considered more robust than Cronbach's Alpha because they take into

Table 4: Correlation matrix

	Attraction	Attrition	Gender	Job quality	Gender x Attraction	Gender x Attrition
Attraction						
Attrition	0.317					
Gender	0.119	0.042				
Job quality	1.324	0.317	0.119			
Gender x Attraction	0.752	0.22	0.061	0.752		
Gender x Attrition	0.228	0.758	0.024	0.228	0.298	

Sources: Author's estimates

The table provided appears to be a correlation matrix, which shows the correlation coefficients between pairs of variables. Correlation coefficients range from -1 to 1, with -1 indicating a perfect negative correlation, 1 indicating a perfect positive correlation, and 0 indicating no correlation.
The correlation between Attraction and Attrition is 0.317, suggesting a moderate positive relationship. This could mean that as attraction to the organization increases, attrition (the likelihood of leaving the organization) also tends to increase. The correlation between Attraction and Gender is 0.119, and between Attrition and Gender is 0.042. These are relatively low correlations, suggesting that gender has a weak relationship with both attraction and attrition.

The correlation between Attraction and Job Quality is 1.324. This is unusual, as correlation coefficients should not exceed
1. This might be a data error that needs to be checked. The correlations between the interaction terms (Gender x Attraction, Gender x Attrition) and the other variables are also provided. These correlations can help understand whether the relationships between Attraction/Attrition and the other variables differ based on gender.
In conclusion, this research appears to be exploring important questions about employee attraction, attrition, and job quality, and how these constructs are related to gender.

Table 5: Variance Inflation Factor

Attraction -> Job quality	1.869
Attrition -> Job quality	1.992
Gender -> Job quality	1.006
Gender x Attraction -> Job quality	1.908
Gender x Attrition -> Job quality	2.035

Sources: Author's estimates

The table 5 shows the Variance Inflation Factor (VIF) for each predictor in a regression model predicting Job Quality. VIF is a measure of multicollinearity among the predictors in a regression model. Multicollinearity refers to the situation in which two or more predictors in a model are highly correlated, making it difficult to determine the individual effects of the predictors.

Here's a brief explanation of each VIF:
Attraction -> Job quality: The VIF of 1.869 suggests that there is some correlation between Attraction and the other predictors in the model, but it is not so high as to cause major concerns about multicollinearity. Attrition -> Job quality: The VIF of 1.992 is slightly higher, indicating a higher degree of correlation between Attrition and the other predictors.
Gender -> Job quality: The VIF of 1.006 is very close to 1, which suggests that Gender is not correlated with the other predictors in the model. Gender x Attraction -> Job quality: The VIF of 1.908 suggests some correlation between the interaction term Gender x Attraction and the other predictors. Gender x Attrition -> Job quality: The VIF of 2.035 is the highest among the predictors, indicating the highest degree of correlation with the other predictors.

In general, a VIF above 5 or 10 is often considered a cause for concern. In this case, all the VIFs are below these thresholds, suggesting that multicollinearity is not a major issue in your model. However, the relatively higher VIFs for Attrition and the interaction terms suggest that these predictors have more shared variance with the other predictors in the model compared to Attraction and Gender. This could potentially make it more difficult to interpret the individual effects of these predictors on Job Quality.

III. CONCLUSION

The study explores the impact of demographic variables on employee performance, highlighting the importance of age, gender, education, and experience. It emphasizes the need for gender diversity, higher education, and job experience in HR strategies. The research method involves quantitative analysis of numerical data and statistical linkages. The study uses stratified random sampling to examine the link between People Analytics and Employee Performance using regression analysis and moderation analysis. It uses PLS- SEM for data analysis, focusing on informed permission, data protection, and confidentiality. Early data shows reliable and valid measuring equipment, but issues like perfect R-square for Job Quality and unexpected correlation values need further investigation.

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